Development of Function-Related Groups Version 2.0: A Classification System for Medical Rehabilitation

Margaret G. Stineman, Charles J. Tassoni, José J. Escarce, James E. Goin, Carl V. Granger, Roger C. Fiedler, and Sankey V. Williams

Objective. To present a new version (2.0) of the Functional Independence Measure–Function Related Group (FIM–FRG) case-mix measure.

Data Source/Study Setting. 85,447 patient discharges from 252 freestanding facilities and hospital units contained in the 1992 Uniform Data System for Medical Rehabilitation.

Study Design. Patient impairment category, functional status at admission to rehabilitation, and patient age were used to develop groups that were homogeneous with respect to length of stay. Within each impairment category patients were randomly assigned to one data set to create the system (through recursive partitioning) or a second set for validation. Clinical and statistical criteria were used to increase the percentage of patients classified, expand the impairment categories of FIM–FRGs Version 1.1, and evaluate the incremental predictive ability of coexisting medical diagnoses. Predictive stability over time was evaluated using 1990 discharges.

Principal Findings. In Version 2.0, the percentage of patients classified was increased to 92 percent. Version 2.0 includes two new impairment categories and separate groups for patients admitted to rehabilitation for evaluation only. Coexisting medical diagnoses did not improve LOS prediction. The system explains 31.7 percent of the variance in the logarithm of LOS in the 1992 validation sample, and 31.0 percent in 1990 discharges.

Conclusions. FIM–FRGs Version 2.0 includes more specific impairment categories, classifies a higher percentage of patient discharges, and appears sufficiently stable over time to form the basis of a payment system for inpatient medical rehabilitation.

Key Words. Activities of daily living, case mix, rehabilitation, resource allocation, function-related groups

Payment for inpatient medical rehabilitation remains exempt from Medicare's prospective payment system. Under the Tax Equity and Fiscal Responsibility Act of 1982 (TEFRA, PL 97-248), Medicare reimburses inpatient rehabilitation for reasonable costs per hospital discharge up to a maximum amount. This amount, called the TEFRA target-rate limit, is established separately for each facility based on average costs per discharge during a base year. However, because the legislated annual increases in TEFRA limits have not kept up with the rate of inflation in facility costs, older facilities with earlier base years receive lower payments than newer facilities (Coopers and Lybrand 1985). TEFRA payments also fail to account for impairment and functional status, thereby providing financial incentives to admit preferentially the least disabled and least costly patients. Problems with the TEFRA system have sparked considerable interest in the development of an alternative payment system for rehabilitation facilities. The Secretary of Health and Human Services, in response to provisions in the Omnibus Budget Reconciliation Act of 1990 (PL 101–508), has called for proposals to restructure Medicare's payment system for inpatient rehabilitation facilities.

Several alternative payment approaches for medical rehabilitation have been suggested (Batavia 1985; Coopers and Lybrand 1985; Harada, Kominski, and Sofaer 1993; Hosek, Kane, Carney, et al. 1986; Langenbrunner, Willis, Jencks, et al. 1989), but a system of case-based prospective payment would be most consistent with Medicare's current payments to acute care hospitals. Developing this payment system requires a method for classifying patients according to their use of rehabilitation resources (Coopers and Lybrand 1985; Langenbrunner, Willis, Jencks, et al. 1989). We developed such a system, based primarily on the impairment for which the patient was receiving

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Address correspondence and requests for reprints to Margaret G. Stineman, M.D., Associate Professor of Rehabilitation Medicine, University of Pennsylvania Medical Center, 3615 Chestnut Street, Room 101, Philadelphia, PA 19104-2676. Charles J. Tassoni, Ph.D. is senior programmer, Robert Wood Johnson Pharmaceutical Research Foundation, Raritan, NJ; Dr. Tassoni was a project manager in the Department of Rehabilitation Medicine, University of Pennsylvania, at the time this research was conducted. José J. Escarce, M.D., Ph.D. is assistant professor of medicine, University of Pennsylvania; James E. Goin, Ph.D. is president and statistician, Data Medix; Carl V. Granger, M.D. is professor of rehabilitation medicine, State University of New York at Buffalo; Roger C. Fiedler, Ph.D. is director of research, Uniform Data System for Medical Rehabilitation, State University of New York at Buffalo; and Sankey V. Williams, M.D. is Sol Katz Professor of Medicine and professor of health care systems, University of Pennsylvania.
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rehabilitation and functional status at admission. Functional status was measured using the Functional Independence Measure (FIM^{SM}) (Uniform Data System for Medical Rehabilitation [UDSMR^{SM}] 1990; Hamilton, Granger, Sherwin, et al. 1987). The system, called FIM–Function Related Groups (FIM–FRGs) Version 1.1 (Stineman, Escarce, Goin, et al. 1994), classifies patients into groups that are homogeneous with respect to rehabilitation length of stay (LOS).[1] Version 1.1 included 53 patient groups and explained 31.3 percent of the variance in the natural logarithm of LOS.

Following completion of FIM–FRGs Version 1.1, several issues remained that could affect the clinical acceptability of the system and its applicability for use in a payment system. Specifically, Version 1.1 excluded 19 percent of patients. To be useful for payment, a patient classification system must classify nearly all patients. In addition, owing to sample size limitations, Version 1.1 combined certain clinically distinct impairments that could reduce its clinical interpretability. Similarly, coexisting medical diagnoses, including etiology, manifestations, comorbidities, and complications, were not considered in the development of Version 1.1. Finally, the stability over time of Version 1.1 was not addressed. Because classification systems designed for payment use historical data to predict resource use in future years, such stability is essential.

In this article we report the results of our attempts to refine the FIM–FRGs by:

1. Expanding the inclusion criteria to accommodate a larger percentage of patients presenting to rehabilitation while still maintaining the explanatory ability of the system.
2. Enhancing the clinical specificity of the impairment categories.
3. Exploring the incremental predictive ability of coexisting medical diagnoses as represented by ICD-9-CM codes.
4. Evaluating the classification system's stability over time.

DATA AND METHODS

FIM–FRGS VERSION 1.1

FIM–FRGs Version 1.1 was developed from data collected by the Uniform Data System for Medical Rehabilitation (UDSMR) between January 1, 1990 and April 19, 1991. It included discharges from 125 freestanding rehabilitation facilities and hospital units. We used clinical criteria (Stineman, Escarce, Goin, et al. 1994) to exclude patients whose rehabilitation was considered atypical. Exclusion criteria consisted of very long or short LOS, age less than 16 years, readmission to rehabilitation after a previous stay, discharge to acute medical or surgical services without return to rehabilitation within 30 days, admission for evaluation only, discharge to a different rehabilitation facility, or death during rehabilitation. The statistical approach to classification was based on recursive partitioning.

FIM–FRGs Version 1.1 classified patients based on three broad characteristics: impairment, disability, and age. Patients were first classified into one of 18 mutually exclusive rehabilitation impairment categories (e.g., stroke, traumatic brain injury, etc.). They were then further divided by level of disability at admission to rehabilitation and age. Disability was measured by the FIM (UDSMR 1990), a standard measure of the type and amount of human assistance required by a person with disability to perform basic life activities. The FIM is completed by clinicians at admission and discharge. It consists of 18 items, each of which is assigned a score (performance level) from 1 to 7 using standard definitions (lower values indicate greater disability) (UDSMR 1990). The FIM has good interrater reliability (Hamilton et al. 1994) and is composed of two distinct domains: motor and cognitive (Linacre, Heinemann, Wright, et al. 1994; Stineman, Shea, Jette, et al. 1996). The motor–FIM measures physical activities and contains eating, grooming, bathing, dressing upper body, dressing lower body, toileting, bladder and bowel management, bed/chair/wheelchair transfer, toilet transfer, tub/shower transfer, walk/wheelchair locomotion, and stair climbing. The cognitive–FIM measures comprehension, expression, social interaction, problem solving, and memory. Previous work has confirmed that the FIM–FRGs based on the motor- and cognitive–FIM subscales are superior to FIM–FRGs based on various other groupings of FIM items (Stineman, Hamilton, Granger, et al. 1994).

SAMPLING STRATEGY FOR FIM-FRGS VERSION 2.0

The UDSMR database was used for the development of FIM–FRGs (Version 2.0). Included were patients discharged from 252 medical rehabilitation facilities between January 1 and December 31, 1992. To enhance data quality, analysis was limited to those facilities in the UDSMR in which all clinicians responsible for coding the FIM scored at least 80 percent on a written examination designed to test competence of coding. Patient records that were obviously miscoded, had incomplete information for any of the variables used for FRG classification, or were missing basic demographic information were deleted, leaving 92,705 (98.8 percent) of the original 93,829 patients.

INCREASING THE PERCENTAGE OF PATIENTS CLASSIFIED

Based on Version 1.1 exclusion criteria, patients who had LOS greater than 365 days ($n = 29$), were in rehabilitation three days or less ($n = 1{,}090$), were less than 16 years of age ($n = 317$), were discharged to another rehabilitation facility ($n = 431$), or died during rehabilitation ($n = 270$) were removed, leaving 90,568 patients. Patients in the three largest exclusion categories (designated in Version 1.1) were examined for possible inclusion in Version 2.0. These categories were rehabilitation readmissions (7 percent of discharges),[2] patients discharged from rehabilitation to acute medical or surgical services who did not return to rehabilitation within 30 days (5 percent of discharges), and patients admitted for evaluation only (less than 1 percent of discharges). Two statistical analyses were performed on each exclusion category. The first analysis evaluated the extent to which mean LOS, calculated within-FRG, differed between excluded and included patients using Version 1.1 to classify patients. The second analysis evaluated whether the expected relationship between greater severity of disability and longer LOS was maintained in the excluded categories. These analyses were based primarily on 1990 discharges but were confirmed using the 1992 data. Among the 1990 discharges there were 32,422 patients who met Version 1.1 inclusion criteria; 3,329 rehabilitation readmissions; 2,703 patients discharged from rehabilitation to acute medical or surgical services who did not return to rehabilitation within 30 days; and 681 patients admitted for evaluation only.

REEVALUATING THE IMPAIRMENT CATEGORIES

Owing to sample size limitations, impairment categories in Version 1.1 were based on combining certain related impairments, resulting in a clinically heterogeneous mix of patients in some categories. For example, two clinically distinct impairments, multiple sclerosis and Guillain-Barré syndrome, were included in a general neurological impairment category. The goal in refining the impairment categories for Version 2.0 was to increase impairment specificity by reducing heterogeneity while maintaining sufficient cases in each category to provide statistical stability of classification. Based on advisory panel recommendations, three further divisions were explored in the existing impairment categories: (1) removing burns and congenital impairments from the larger "miscellaneous" category so that each formed a new category;

(2) removing multiple sclerosis and Guillain-Barré from the neurological category so that each formed a new category; and (3) splitting the major multiple trauma category into two categories: one that included patients with any combination of brain and/or spinal cord injury and one that included all other major multiple trauma patients.

STATISTICAL APPROACH TO CLASSIFICATION

All variables collected by UDSMR were reviewed for possible use in classifying patients. As part of this review, cross-tabulations (for categorical variables) and correlations (for continuous variables) were used to assess the associations between the variables and LOS. Because payment is an intended use of the classification system, we excluded variables that could be manipulated for financial gain or that were difficult to pinpoint temporally (temporary transfers to acute care services, and time elapsed since onset of disability). Following these analyses, we selected the same classifying variables as in version 1.1: motor–FIM, cognitive–FIM, and age at admission.

Sixty percent of the observations in each impairment category and in the evaluation only category (see below) were randomly selected for model building, and the remaining 40 percent were set aside for validation. Classification rules were derived separately for each category using motor–FIM, cognitive–FIM, and patient age as independent variables. The logarithm of LOS (lnLOS) had a more symmetrical distribution than LOS; consequently, it was used as the dependent variable. Analyses to predict lnLOS were undertaken in the model building sample of each category. The new FRGs were created using a recursive partitioning algorithm called Classification and Regression Trees (CART) (Breiman et al. 1984). Splits resulting in FRGs with fewer than 50 observations in the model building sample were not allowed. The general approach, based on the CART least squares construction rule, was similar to that taken in creating Version 1.1 (Stineman, Escarce, Goin, et al. 1994).

Once completed, predictive ability of the new system was assessed by first developing a linear regression model in the model building sample, with lnLOS as the dependent variable and a set of binary indicator variables corresponding to the candidate FRGs as the independent variables. Cross-validation occurred by applying the estimated coefficients obtained in the model building sample to the validation sample and calculating R-square values for the validation data (Kleinbaum, Kupper, and Muller 1987). R-square values were obtained for the individual impairment categories, for the evaluation only category, and for the entire system.

EVALUATING THE ROLE OF COEXISTING MEDICAL DIAGNOSES IN PREDICTING LOS

Coexisting medical diagnoses, as represented by ICD-9-CM codes, were evaluated for their ability to increase the variance explained in lnLOS beyond elements already in the FIM–FRGs. We took a two-level statistical approach. First, we developed the FIM–FRG groups, using age, motor–FIM, and cognitive–FIM. Next, we coded the resulting groupings and developed a linear regression model with these groupings and coexisting diagnoses. The intent was to develop an index of medical complexity that could be used as an additional classifying variable within the classification algorithm.

The UDSMR collects information for eight fields of ICD-9-CM diagnoses coded at discharge from rehabilitation. The first field refers to the principal diagnosis or etiology related to the patient's impairment category. For example, if the patient's impairment category is stroke, then an appropriate etiology might be intracerebral hemorrhage (ICD-9-CM code 431). The remaining fields describe other impairments, comorbidities, or complications. For this sub-analysis, observations in which there were no entries in any of the eight diagnosis fields on the UDSMR coding sheet, or in which there were gender- and/or age-inappropriate codes or out-of-range values, were removed (2.2 percent records).

Using lnLOS as the dependent variable, three alternative approaches for quantifying the effect of diagnoses were tested through a series of linear regression models. Each regression model included binary indicator variables corresponding to the FRGs in an impairment category, and one of the three alternative approaches for modeling the effect of diagnoses. The first approach used major diagnostic categories (MDCs) to group-related ICD-9-CM codes. The second approach used chapter headings from the *International Classification of Diseases* (Practice Management Information Corporation 1991) to group ICD-9-CM codes. The third approach used an independent variable for each unique ICD-9-CM code that occurred in at least 20 cases in the model-building sample of the impairment category being analyzed. The incremental predictive ability of medical diagnoses was defined as the difference in R-squares as obtained in the validation data before and after including diagnoses in the models.

DETERMINING STABILITY OVER TIME

The stability of the FIM–FRGs Version 2.0 system was tested using 1990 discharge data. Regression models created using lnLOS and the FRG indicator variables in the 1992 model-building sample were cross-validated using this 1990 data. For this analysis, the 1990 data were processed using Version 2.0 case selection criteria. In addition, mean LOS within-FRG was compared across years. This was determined by calculating a weighted average difference between 1990 and 1992 discharges for each FRG, using 1992 as standard. Finally, change in the predictive structure over time was determined by comparing Versions 1.1 and 2.0 prediction rules for the 16 impairment categories in common.

RESULTS

The mean age of patients at admission to rehabilitation was 69.4 (±16.0) years, with mean motor–FIM scores of 47.5 (±16.0) and mean cognitive–FIM scores of 26.3 (±8.7). Patients stayed in rehabilitation an average of 26.3 (±17.0) days. The primary payment source was Medicare for 74.7 percent of discharges.

INCREASING THE PERCENTAGE OF PATIENTS CLASSIFIED

Combining patients across all FRGs, discharges to acute care in 1990 had a mean LOS of 21.6 days, evaluation-only admissions had a mean LOS of 20.0 days, and readmissions had a mean LOS of 26.1 days compared to 27.8 days for included patients. Consistent with these findings, discharges to acute care and evaluation-only admissions had within-FRG LOS means that were shorter than included cases (data not shown). Readmissions had within-FRG LOS means and coefficients of variation similar to those of included patients, and the FRG structure relating to severity of disability was preserved. Patterns were similar for 1992 discharges. Based on these findings, readmissions (not excluded for other reasons) were included in classification, but discharges to acute care ($n = 4{,}935$) were excluded. Because the process of evaluating the potential of patients for rehabilitation differs from the provision of a full rehabilitation program, a separate, non-impairment-specific category was created for the 913 cases not excluded for other reasons. After removing statistical outliers from all categories ($n = 186$), 85,447 patients remained. Thus, 92.2 percent of the 92,705 usable records were included in development of FIM–FRGs Version 2.0, constituting 91.1 percent of all discharges originally in the database.

REEVALUATING THE IMPAIRMENT CATEGORIES

Because of insufficient numbers of burn ($n = 46$) and congenital impairment ($n = 32$) cases in the model building sample, separate impairment categories were not formed. There were, however, sufficient cases for the other proposed separations. Guillain-Barré patients (mean LOS = 40.2) had much longer average LOS than other patients in the neurological impairment category (mean LOS = 23.0). Consequently, we defined Guillain-Barré as a new impairment category, but maintained multiple sclerosis (mean LOS = 24.5) in the general neurological category. Patients with any combination of brain and/or spinal cord injury (mean LOS = 36.1) had longer average LOS than did other patients in the general major multiple trauma category (mean LOS = 25.5) and, therefore, formed a new impairment category.

DERIVING FIM–FRGS VERSION 2.0

Table 1 shows the number of patients available for creating and validating the classification system, the cross-validation R-squares for each of the impairment categories and the evaluation only category, as well as the variables used

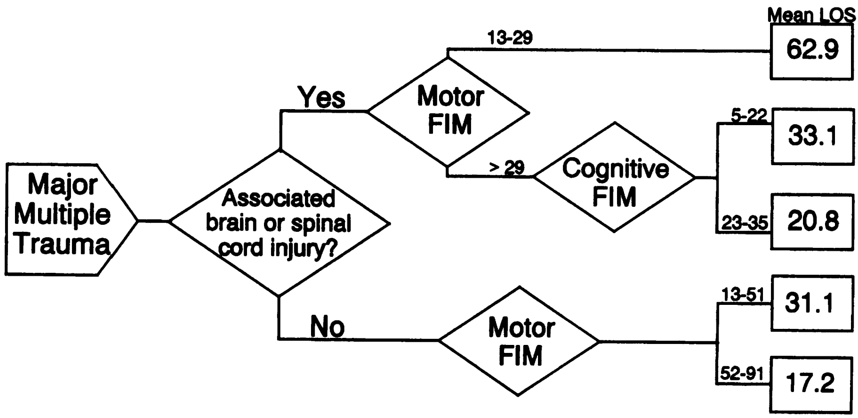
Table 1: Characteristics of FIM–FRGs Version 2.0

Impairment Category	N	*Number of FRGs*	*Variables**	$R^{2\dagger}$
Stroke	26,183	9	M,C,A	.26
Nontraumatic brain	2,513	4	M,A	.24
Traumatic brain	3,214	5	M,C	.32
Nontraumatic spinal cord	2,609	4	M	.23
Traumatic spinal cord	1,831	4	M	.30
Guillain-Barré	388	2	M	.30
Neurological	3,558	2	M	.13
Lower extremity fracture	12,445	4	M,C	.09
Joint replacement	12,658	7	M,C,A	.16
Other orthopedic	3,715	2	M	.08
Lower limb amputation	3,256	2	M	.07
Other amputation	211	1	—	—
Osteoarthritis	1,651	2	M	.12
Rheumatoid arthritis	1,469	2	M	.10
Cardiac	1,038	2	M	.15
Pulmonary	1,075	3	M	.19
Pain	1,591	2	M	.02
Major multiple trauma (MMT)	534	2	M	.18
MMT with brain/spine injury	435	3	M,C	.37
Miscellaneous	4,163	3	M	.15
Evaluation only	910	2	M	.08
Overall System	85,447	67		.32

† M = Motor–FIM; C = Cognitive–FIM; A = Age.

* Cross-validation R^2.

Figure 1: FIM–FRG Grouping Structure for Major Multiple Trauma



to form the FRGs. Version 2.0 has an overall cross-validation R-square of 31.7 percent, and is composed of 20 impairment categories, one evaluation only category, and 67 FRGs. An example of the FIM–FRG grouping structure for major multiple trauma is shown in Figure 1. The major multiple trauma impairments (MMT) were selected to illustrate how the finer 2.0 impairment categories were split from the larger Version 1.1 MMT category. The MMT impairment is split into those with brain and/or spinal cord injury and those without such injuries. Then patients are classified into groups based on motor- and cognitive–FIM scores at rehabilitation admission. The appendix shows the number of observations in each of these FRGs and the mean LOS and standard deviation for the model building and validation samples in each, along with similar data for all FRGs in Version 2.0. It also displays FRGs for the largest impairment category, stroke.

EVALUATING THE ROLE OF COEXISTING MEDICAL DIAGNOSES IN PREDICTING LOS

The incremental predictive ability of the new system was not substantially enhanced by adding information about coexisting medical diagnoses, as represented by ICD-9-CM codes (Table 2). Of the three approaches to quantifying the effect of diagnoses, the ICD-9-CM approach increased variation explained by .02, the MDC approach by .01, and the chapter heading approach by .00 percentage points. Therefore, we did not modify the FIM–FRGs by adding ICD-9-CM codes.

Table 2: Incremental Change in Variance Explained Due to Diagnosis Over and Above FRG Elements

		Incremental Change with Diagnosis		
Impairment Category	*FRG Only*	*ICD-9*	*MDC*	*CHP*
Stroke	.26	.02	.01	.01
Nontraumatic brain	.23	.06	.01	.02
Traumatic brain	.32	.03	.01	.02
Nontraumatic spinal cord	.23	.04	.03	.03
Traumatic spinal cord	.30	.06	.03	.03
Guillain-Barré	.30	.01	.02	.03
Neurological	.13	.03	.02	.02
Lower extremity fracture	.09	.06	.02	.02
Joint replacement	.16	.05	.01	.02
Other orthopedic	.08	.04	.01	.02
Lower limb amputation	.07	.04	.04	.02
Other amputation*	—	—	—	—
Osteoarthritis	.11	.03	.02	.03
Rheumatoid arthritis	.10	.08	.06	.06
Cardiac	.15	.02	.02	.01
Pulmonary	.20	.00	.00	.00
Pain	.02	.05	.04	.03
Major multiple trauma (MMT)	.17	.02	.02	.02
MMT with brain/spine injury	.37	.00	−.01	−.02
Miscellaneous	.15	.02	.03	.02
Overall	.32	.02	.01	.00

* This category consisted of a single FRG; thus, the incremental change in variance is not relevant.

STABILITY OVER TIME

There were 35,249 records from patients discharged in 1990 available for analysis after applying Version 2.0 case selection criteria. Version 2.0 explained 31.0 percent of the variance in the sample of 1990 discharges compared to 31.7 percent in the 1992 validation sample. Moreover, the variance explained by Version 2.0 in the data from 1990 was similar to that explained by Version 1.1 (31.1 percent). Predictive ability of the system was maintained over the different years, even though there was a weighted average decline of 2.1 days in LOS between 1990 and 1992 as calculated across the 67 FRGs. Comparing 1990 to 1992 discharges, the average LOS declined in 63 of the 67 FRGs (see appendix).

The total number of impairment categories increased by two in Version 2.0 in that two of the original categories were subdivided. Sixteen of the 18 original impairment categories remained the same, enabling direct comparison across the two FIM–FRGs versions. The motor–FIM variable was used in 15 of the comparable impairment categories. The only impairment category that did not split on motor–FIM for either version was other amputation, which also did not split on the other two predictor variables. The cognitive–FIM was used in four of the comparable impairment categories in Version 2.0, and in three of those categories in Version 1.1. Only traumatic brain dysfunction had a cognitive–FIM split in both versions. In Version 2.0, age was used in three of the comparable impairment categories, while in Version 1.1, age was used in only one impairment. An age split occurred in the stroke impairment of both versions.

DISCUSSION

We report the development and testing of a new version of the FIM–FRGs (Version 2.0). Version 2.0 classifies a higher percentage of patients than Version 1.1 while maintaining the ability to predict length of stay. Version 2.0 also includes a more clinically relevant and specific set of impairment categories, along with a new category for patients admitted for evaluation only. Adding information about coexisting medical diagnoses (ICD-9-CM codes) to information already contained in the FIM–FRG system did not substantially improve predictive ability. Therefore, Version 2.0 contains the same classifying variables as Version 1.1: impairment category, motor–FIM, cognitive–FIM, and age. It is important to note that the predictive accuracy of the FIM–FRG system for LOS was stable across time, despite declining LOS within nearly all FRGs.

In revising the FIM–FRG system, we were able to improve it in several ways. First, a higher percentage of patients has been accommodated, accounting for 92.2 percent of patient discharges, as compared to 81.3 percent in Version 1.1. This increase is due to the inclusion of readmission and evaluation-only patients formerly excluded from the system. Second, increased specificity of the impairment categories was possible because more data were available to develop Version 2.0. Of the new impairment categories, Guillain-Barré patients tend to have more prolonged periods of neurological recovery and better functional prognoses compared to those with other neurological conditions, such as Parkinson's disease or multiple sclerosis, which are predominantly degenerative. In addition, MMT patients with injury to the spinal cord and/or brain require longer periods of rehabilitation than those without such injury.

Information about the patient's coexisting medical diagnoses did not increase the system's ability to predict LOS. This may be attributed to several factors related to coding, opposing forces, or redundancy of information. For example, medical diagnoses may be potentially useful in predicting LOS; however, present coding conventions and inconsistency of coding across centers may limit the usefulness of information collected. Illnesses represented by ICD-9-CM codes may also have opposing effects on LOS, increasing patient LOS in some cases and causing patients to be discharged prematurely in others. A further explanation may be that information about coexisting medical diagnoses is redundant with information already included in the patient's FIM–FRG (i.e., impairment, functional status, and age). Finally, although they had minimal impact on LOS, our analyses do not exclude the possibility of diagnoses proving helpful in explaining cost variation. For example, patients with particular diagnoses may incur higher daily treatment costs without requiring an increase in the total days of care.

A patient classification system must predict accurately across time if it is to serve as the basis for a payment system. Our analyses showed that Version 2.0 predicted resource use in 1990 almost as well as it did in 1992. The predictive ability of the system was maintained despite LOS in 1992 being shorter than in 1990. This reduction in LOS was fairly uniform across nearly all of the individual FRGs. The predictive associations among the clinical variables and lnLOS were similar in the two versions. As in Version 1.1, the predominant association was between greater physical disability, as expressed by the motor–FIM, and longer LOS, but in one out of the 36 instances where the motor–FIM was partitioned, greater disability was associated with shorter LOS. This tendency toward an inverse relationship occurred in none of the Version 1.1 splits. Additionally, greater disability was associated with shorter LOS in two of seven cognitive–FIM splits in Version 2.0, but in none of the cognitive–FIM splits in Version 1.1.

The slight trend toward an inverse relationship between functional severity and LOS might reflect real changes in rehabilitation care. Rising rehabilitation costs (Aitchison 1993) may pressure facilities to look for ways to increase efficiency. One response to this pressure may be to discharge patients whose disability is so great that they have less chance of improving quickly. Alternatively, it may be that the greater number of observations in Version 2.0 allowed finer classification distinctions. Assuming that the predictive trends are real, some might argue that older people and those with greater disability have less functional reserve and require longer periods of rehabilitation to achieve the same degree of recovery. Others might argue that if these individuals show fewer gains during rehabilitation, then quicker discharge is justified since their progress stops at lower functional levels. Distinguishing among these alternative interpretations will require further studies.

A patient classification system is distinct from a payment system, and is only one of potentially many components of the payment formula. As in the DRG-based prospective payment system, it may be necessary to adjust FIM–FRG payment to reflect differences in local wage rates, facility type, teaching programs, or urban/rural status. Moreover, as in the development of the DRG classification system, the structure of FIM–FRGs may have been influenced by the existing payment system. Clinicians in certain types of facilities might have been forced to respond to cost pressures by changing admission criteria, or treatment strategies. Thus the FIM–FRGs reflect 1992 practice patterns, not necessarily optimal practices.

In conclusion, Version 2.0 of the FIM–FRGs includes a larger percentage of rehabilitation discharges and more specific impairment categories than Version 1.1. Coexisting medical diagnoses were not added to the system because they did not improve predictive ability. Finally, the ability of the system to predict LOS was maintained over a period of two years. The expanded number of impairment categories makes Version 2.0 more clinically coherent. The inclusion of a higher percentage of rehabilitation discharges makes the system more widely applicable and the stability of predictions over time supports the feasibility of future applications for payment.

Appendix: Mean Length of Stay and Standard Deviation: Comparing the Model Building, Validation, and 1990 Samples for Version 2.0

		1992 Model Building			*1992 Validation*			*1990 Data Set*		
	FRG	*N*	*Mean*	*STD*	*N*	*Mean*	*STD*	*N*	*Mean*	*STD*
Stroke	1	3,381	37.7	17.2	2,271	38.2	17.6	2,975	40.8	19.6
	2	1,717	30.2	15.3	1,139	30.6	15.6	1,317	32.9	17.7
	3	1,360	33.7	14.7	955	34.0	15.1	1,136	35.0	16.2
	4	3,879	28.2	12.9	2,529	28.3	12.2	3,177	31.1	14.2
	5	2,245	23.0	11.0	1,570	22.1	9.9	1,812	25.1	11.7
	6	1,559	19.2	8.6	1,022	19.5	9.8	1,305	21.1	10.5
	7	925	16.9	10.2	641	17.0	9.9	819	18.1	9.5
	8	449	14.8	7.5	301	14.3	6.9	368	15.9	8.4
	9	150	10.5	7.1	90	11.9	6.2	136	11.8	7.3
Nontraumatic brain	1	258	52.7	31.7	147	52.5	31.4	143	53.2	34.4
	2	400	34.0	19.6	261	33.7	18.1	241	38.1	25.8
	3	480	25.5	14.7	344	25.6	14.3	334	29.5	19.9
	4	383	20.1	15.6	240	19.9	14.3	264	20.6	12.0
Traumatic brain	1	288	78.3	53.6	194	80.9	55.0	274	96.8	69.8
	2	424	46.2	29.2	319	47.0	31.4	431	54.7	37.3
	3	757	29.0	22.1	508	30.5	25.7	733	33.0	26.0
	4	324	20.7	15.0	185	21.0	23.6	262	21.9	16.6
	5	131	13.4	8.2	84	17.2	12.6	155	17.2	13.9
Nontraumatic spinal cord	1	483	40.6	23.9	351	37.5	22.1	327	45.3	29.2
	2	313	28.2	16.5	175	31.5	20.0	208	31.9	19.0
	3	492	21.3	12.7	303	21.8	12.4	351	24.5	15.2
	4	276	15.8	11.4	216	16.1	9.4	213	18.5	13.1

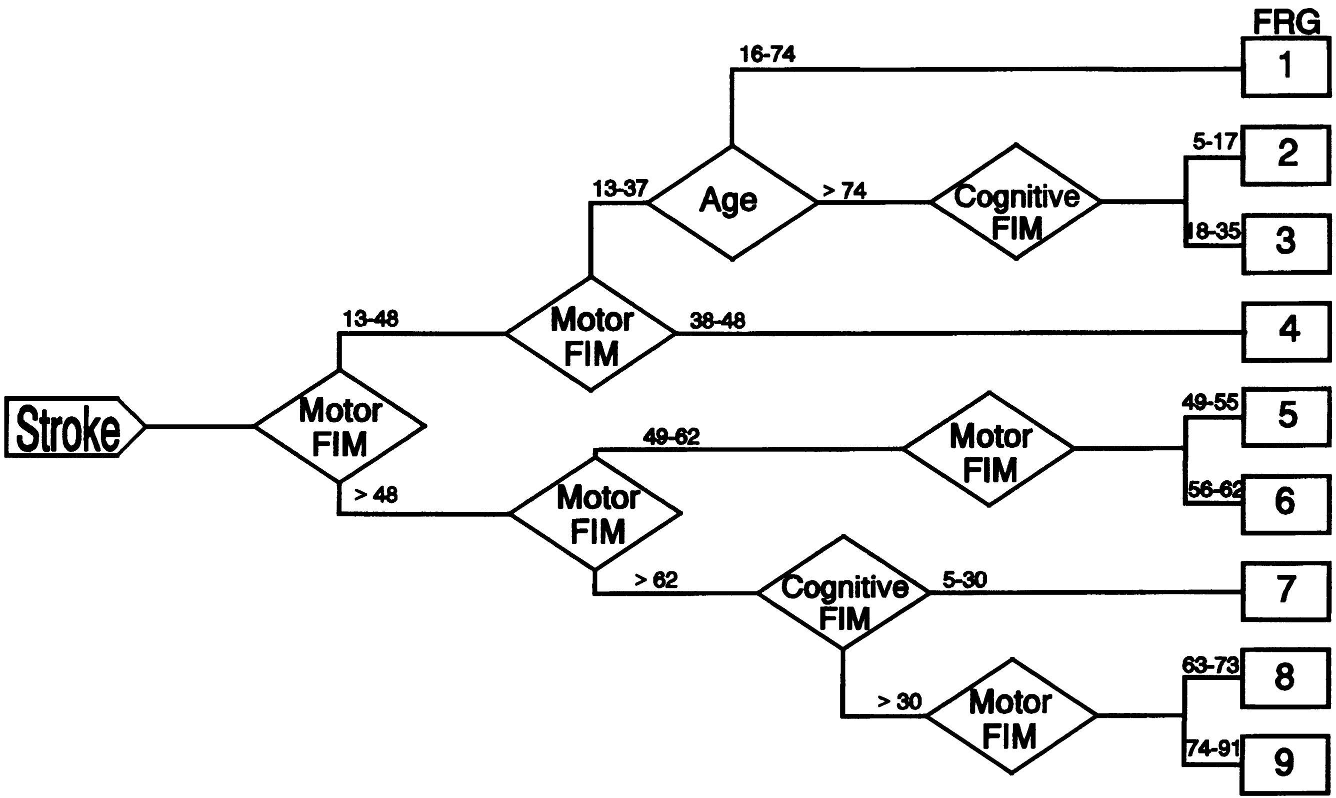
Continued

Appendix: Continued

		1992 Model Building			*1992 Validation*			*1990 Data Set*		
	FRG	*N*	*Mean*	*STD*	*N*	*Mean*	*STD*	*N*	*Mean*	*STD*
Traumatic spinal cord	1	184	76.0	48.2	142	77.2	46.3	230	85.1	50.1
	2	331	50.9	34.9	201	53.0	38.3	351	56.9	34.7
	3	349	35.1	24.9	248	33.3	22.5	381	38.3	21.0
	4	219	22.4	18.3	157	21.4	15.8	205	25.0	19.6
Guillain-Barré	1	136	54.2	36.8	73	49.3	31.2	76	57.6	42.8
	2	103	22.0	18.6	76	22.7	16.3	87	22.4	12.7
Neurological	1	1,412	26.4	14.8	895	25.9	13.5	699	27.7	16.0
	2	750	17.7	9.9	501	17.3	9.8	404	18.4	10.0
Lower extremity fracture	1	148	17.3	10.4	83	20.2	11.7	89	22.9	11.6
	2	2,115	24.4	10.7	1,393	24.5	10.8	979	24.5	10.8
	3	2,568	20.9	8.9	1,598	21.3	9.5	1,182	21.9	9.3
	4	2,786	17.2	8.2	1,754	17.4	8.2	1,424	18.0	8.0
Joint replacement	1	65	10.9	8.1	51	12.2	7.2	11	23.2	10.9
	2	1,433	21.2	9.1	983	20.7	9.4	639	22.4	9.6
	3	1,898	15.7	6.8	1,308	15.7	6.9	742	17.4	7.2
	4	673	18.1	7.2	421	17.5	7.1	282	19.6	8.0
	5	793	14.7	6.5	548	15.2	7.0	400	16.0	7.3
	6	1,708	13.1	5.9	1,165	13.1	5.8	678	15.4	6.4
	7	951	11.1	4.9	661	11.4	5.0	478	12.5	5.6
Other orthopedic	1	1,202	22.2	11.0	823	22.0	10.7	523	23.3	11.6
	2	1,013	16.2	8.3	677	16.5	8.7	484	17.5	9.3
Lower extremity amputation	1	957	27.2	12.7	700	27.1	12.3	715	31.1	16.6
	2	984	21.2	11.6	615	21.6	12.3	920	23.8	13.5

Other amputation	1	122	23.0	14.2	89	21.7	14.3	106	25.3	15.9
Osteoarthritis	1	459	20.3	10.1	312	19.1	9.3	458	20.5	9.7
	2	526	13.6	6.4	354	13.5	7.1	546	16.0	7.5
Rheumatoid arthritis	1	346	23.9	13.0	240	22.5	12.3	246	23.6	11.0
	2	532	15.4	7.6	351	16.1	9.0	369	17.1	9.1
Cardiac	1	211	24.4	13.0	173	24.3	11.9	109	23.4	12.0
	2	368	15.5	7.5	286	16.2	7.7	200	17.7	8.5
Pulmonary	1	61	41.0	24.5	46	40.0	21.2	42	37.3	23.2
	2	285	23.0	11.0	209	23.7	12.4	154	23.9	12.8
	3	286	16.5	8.1	188	17.0	7.7	204	16.9	8.6
Pain syndrome	1	190	22.3	10.5	111	22.1	11.2	141	23.6	12.5
	2	814	16.9	8.2	476	18.4	9.2	902	17.4	9.5
Major multiple trauma (MMT)	1	199	31.1	19.9	116	28.3	18.1	97	33.8	21.5
	2	130	17.2	12.8	89	16.9	10.7	77	19.3	12.2
MMT with brain/spine	1	75	62.9	38.8	56	65.4	43.8	35	84.0	57.4
	2	73	33.1	14.7	45	33.5	17.7	35	32.9	18.8
	3	111	20.8	12.6	75	22.9	12.8	63	27.7	22.0
Miscellaneous	1	972	25.3	13.0	752	25.2	12.7	729	27.3	15.3
	2	968	18.9	9.1	698	18.7	8.6	766	21.1	11.3
	3	493	15.2	8.4	280	14.5	7.7	455	15.9	8.7
Evaluation only	1	368	19.5	12.7	245	20.3	16.3	398	23.4	13.9
	2	172	11.7	9.3	125	11.7	6.6	157	14.4	8.1

Appendix Figure A.1: FRGs for Stroke



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NOTES

1. Although total hospital charges were available, LOS was selected as a proxy for resource use because we believed that LOS would be less influenced by facility pricing policies and local economies. The correlation between LOS and total charges was 0.89.
2. The LOS for readmission cases counted only the days associated with the readmission. To be defined as a readmission, 30 days would need to have elapsed between the previous stay and the readmission.

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